Chapter 3

A Control Systems Engineering Approach to Designing an Effective Lecturing Model: The Implication of Feedback and Self-Construction of Knowledge

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Control systems engineering approaches have seldom been used as an analytical tool in pedagogical research for modelling, analysing and/or designing effective educational processes, despite its proven benefits in other social sciences, especially economics and finance. In this work, we use the elements of open-loop and closed-loop feedback systems to evaluate two modes of teaching and lecturing. The first is the open-loop lecturing mode, which still dominates in many European universities, whereas the second is the so-called closed-loop lecturing mode with feedback and reflection. We provide mathematical models and apply control engineering techniques and tools to analyse the properties of the two lecturing modes. We show that the learning and information retention dynamics differ considerably between the two modes. Furthermore, we show how the closed-loop lecturing mode supersedes the open-loop lecturing mode. The simulation results demonstrate that with lecturing, improved higher educational performance can be attained by fostering self-reflection and will require continuous feedback and reflection.

INTRODUCTION

Control systems engineering methods have been used in non-traditional disciplines such as biology [1], economics [2], finance [3], policy [4], management [5], software engineering [6], Internet engineering [7], physics [8] and psychology [9]. These methods are much less used for conceptual or analytical analysis and design in pedagogy [10, 11].

This could be related to educationalists' reluctance and scepticism of using mathematical models to describe pedagogical processes [12].

Simon argues that mapping qualitative or conceptual models of socio-psychological theories into analytical quantitative models probably enhances the original theories [13]. Explaining a descriptive theory in mathematical models by using analytical evidence could strengthen or degrade claims that are unverified through empirical studies. Mathematical models are more precise than descriptive or conceptual models. Furthermore, using control theory methods for modelling socio-psychological behaviour could lead to the proposal of using control techniques for effectively steering the process outcomes towards the intended objectives, e.g. an engineering approach. Most pedagogical models are conceptual or static. However, learning is a dynamic process in principle. Dynamical models are superior because they show the transition of state over time and allow future predictions of that state. Furthermore, dynamical models enable access to control techniques, which can significantly improve process behaviour. In this paper, an investigation of modelling learning with control systems methods is discussed.

The developed models describe, in a conceptual but mathematical way, the learning process dynamics of two different modes of teaching/learning: open- and closed-loop (e.g. without or with feedback). They also allow computer simulations of the learning process given a specific didactic mode. The simulations, however, do not describe the point-to-point exact progress of the learner knowledge construction level. Rather, they show predictions of the dynamics of each mode. These particular analysis tools are absent in instructional design research. In the next sections, the case is presented of developing mathematical models of the two modes of learning using control systems engineering.

MODELLING A LECTURE: THE OPEN- AND CLOSED-LOOP APPROACH

Traditional lecturing models have generally adopted an open-loop mode, in which the teacher conducts a lecture, lasting approximately an hour, in which material is presented to the students. Feedback is seldom practised in the classroom [14]. Feedback practice during the lecture (in any form) is significantly more likely for teachers who have received teaching training compared to those who have not; however, the provision of elaborated feedback about a task (FT) is low in both cases [15]. This explains the lack of feedback practices in engineering and science higher education courses, where the lecturers have seldom received educational training [16]. Engineering lectures are generally of a passive nature [17]. The lecturing process usually continues as a passive transmitter-receiver model during the semester, without real evaluation of the students' comprehension of the lectures, i.e. there are no frequent formative assessment practices. As a consequence, students are unlikely to voluntarily reflect on the lectures. This results in poor comprehension as well as increased cognitive load during the semester as the lecture content becomes more complex and dependent on material taught previously. A single measurement takes place at the end of the semester when the students take the final exam. This type of measurement is called summative assessment.

In general, the lecturing process can be implemented in a spectrum of ways which span over an axis of two extremes. One extreme is the open-loop teacher-centred approach (classical), while the opposite extreme is a closed-loop or student-centred approach (modern/constructivist). Teacher-centred lecturing is basically a passive transmitter (teacher)–receiver (student) model. Knowledge delivery in this model takes place in the form of narration and passive presentation of the taught material. The main assumption under this mode of teaching and learning is that the students will be able to assimilate the transmitted information completely in their minds just because they received it through their senses. Such an approach without continuous assessment of the students' learning outcomes and without and any involvement of the students in constructing knowledge is an open-loop process from control engineering perspective. On the other hand, reflection, assessment and feedback are important characteristics of constructivist learning [18], which should be considered for implementing an effective lecturing model. Modern constructivist approaches emphasize that it should be made clear to students that they have to practise and that they are knowledge constructers, whilst the teacher's role is to coordinate the learning process. Recent studies suggest that constructivist approaches such as experiential learning, project based learning, etc., are effective in engineering education and are recommended to migrate to [19, 20, 21]. When it comes to the lecturing process, relevant teaching and learning techniques should be followed to guarantee the student-centred constructivist approach and the successful loop closure alongside the semester progress. A lecturing model that is student-centred with teacher guidance and involves effective feedback would conform to a closed-loop process from a control systems perspective.

Modelling an Open-Loop Lecture

The perception of learning as a simple accumulation process based on teacher transmission (e.g. open-loop learning) was dominant in the pedagogical literature until two decades ago [22]. Since a lecture aims, in general, to accumulate a new piece of knowledge, modelling can be made analogously with an engineering accumulating process, for instance electrical capacity charging or tank filling. Let's use the tank filling process as an example to demonstrate the model's derivation. The tank is filled through a pump that transfers the liquid from a source, e.g. water pipes. The input to the tank is the flow rate out of the pump; this flow rate accumulates the liquid in the tank and causes the liquid level to rise. The varying liquid level is the system output and the quantity is dependent on two main factors: the input flow rate and the tank itself, e.g. its dimensions and shape etc. The classically taught lecture is a process where the teacher (the pump) delivers information at a specific rate (input flow rate). This information is assumed to accumulate in the students' mind (tank). Generally, the teacher will design the lecture and the information delivery rate in a way that it is assumed will reach a specific level by the end. However, in the classical lecturing approach there is no such feedback, e.g. assessment and evaluation that indicates what level has been accomplished (what information has been successfully learned). The analogy between the open-loop filling tank system and the classical teaching and learning approach is shown in Figure 1.

One can write the model specifying the relationship between the teacher input and the transmitted information in a classically taught lecture as follows:

$$\frac{dx}{dt} = au \qquad (1)$$

where x represents the accumulated knowledge, u is the teacher's input that determines the speed of information transmission (in other words, the teaching speed) and "a" is a variable that differs from one learning task to another and from one student to another. In the general, simple case, this factor is considered constant. This constant represents the students' presumed average capability to digest the taught information in a lecture. The

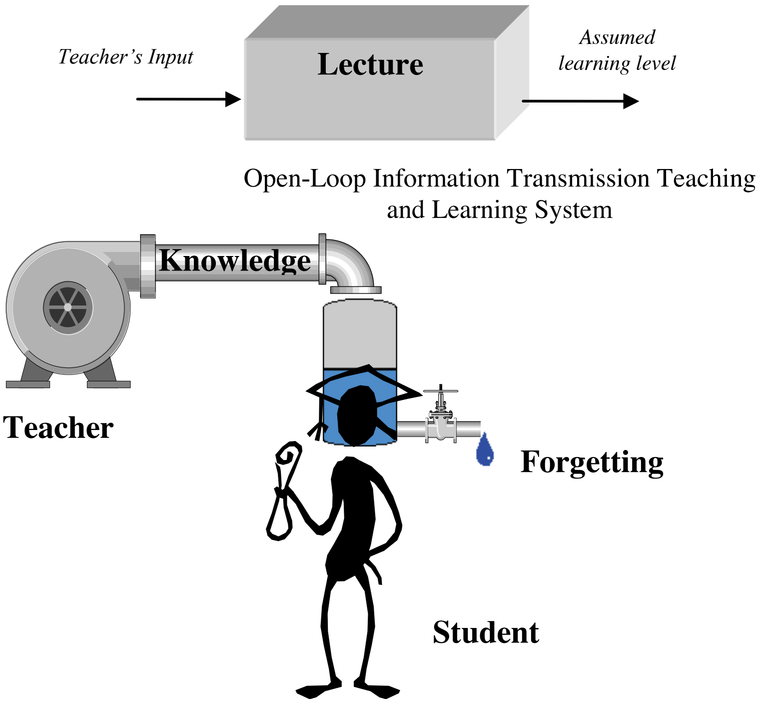

FIGURE 1
ENGINEERING METAPHOR OF OPEN LOOP INFORMATION TRANSMISSION

variable x represents the assumed integrated knowledge in the students' minds as being identical to that delivered by the teacher without any loss or decay. In this model, what is really described is 'Knowledge Transmission' but not necessarily the actual 'Learning'. From this model it is evident that the main controller of the learning process is the teacher, and it is only possible to follow an open-loop control strategy.

Let's assume that the actual learning ability (accumulating knowledge or achieving progress) in the passive lecturing mode for a student is about 50% weaker than the presumed average of the class, i.e. the constant "a" is 50% less. In this case, there will be 50% less progress in the knowledge transmission process. Simulations of the model in Equation (1) for the average and the weak students are shown in Figure 2. The teacher will adjust the information transmission process input (e.g. the teaching rate) so that it delivers a learning unit during a specified time (let's say one hour, as in lectures) according to the average students' capability of information retention that he or she expects.

However, a weaker student with half the capability of the average will hold only half of the delivered information, shown in Figure 2. Since the teacher has no means of assessing how much of the transmitted information has been learnt by the weak student, the information delivery rate will probably not be re-adjusted (the variable u in Equation (1)) to adapt to the weak student's needs.

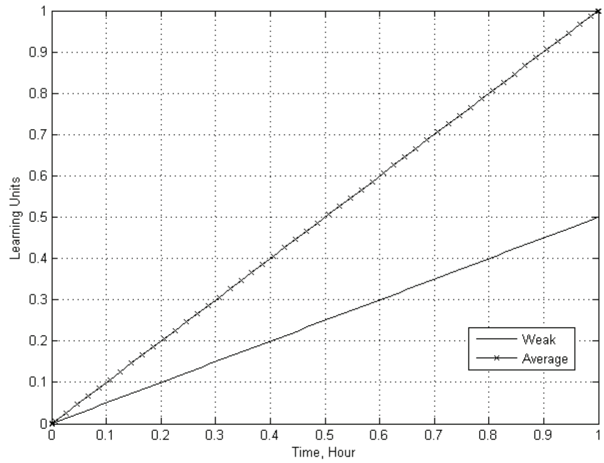

FIGURE 2

SIMULATION OF A LOW CAPABILITY STUDENT'S ACHIEVEMENT VS. AN AVERAGE STUDENT'S ACHIEVEMENT IN AN OPEN-LOOP LEARNING MODE

There are many factors that affect what is actually learned of the transmitted knowledge; the forgetting factor in particular has a profound impact. The impact of the forgetting factor on information retention has been comprehensively studied in cognitive science. The forgetting factor was originally proposed by the German psychologist Herman Ebbinghaus [23].

Ebbinghaus found that humans forget information exponentially. Many models, mainly exponential or power based, were proposed later, and examples of these models can be found in other researchers works [24 - 27]. All of these models share the common features that the forgetting rate is higher for information learnt recently and that the rate declines with time. An empirical comparison of different forgetting factors can be found in the work of [28]. The forgetting rate can increase for many reasons, such as when learning complicated tasks [29], when the learner has a negative mood [30], lack of testing and assessment [31], lack of sleep [32] and drinking alcohol prior to learning [33]. Let's consider the simplest exponential forgetting model of Ebbinghaus [23], which is given by the following:

$$m(t) = c\, e^{-bt} \tag{2}$$

Where m is the remembered information over time, b is the saving rate and c is the amount of remembered information at the start. The element b is affected by many factors such as the complexity of the taught material, stress, lack of sleep and the relationship of the learnt material with previously stored information in the long-term memory etc.

In the case of an open-loop lecture, where information is received once and not reviewed, the retained information in the learner's mind is strongly affected by the forgetting factor. Hence, the forgetting curve described in Equation (2) should be

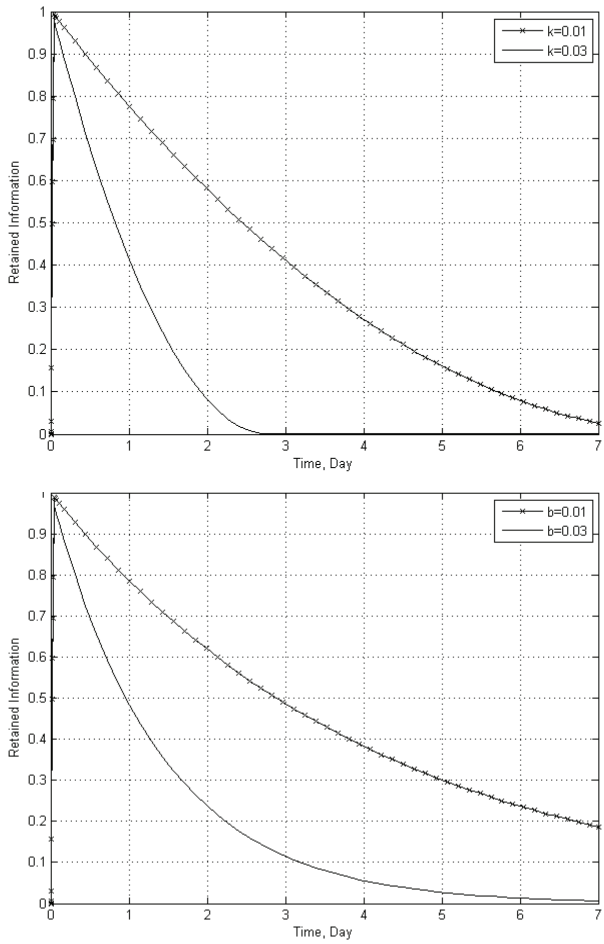

FIGURE 3
THE IMPACT OF THE FORGETTING FACTOR ON INFORMATION RETENTION: ENGINEERING MODEL (TOP) AND COGNITIVE PSYCHOLOGY MODEL (BOTTOM). THE CURVES SIMULATE THE FORGETTING PHENOMENA FOR DIFFERENT VALUES OF THE FORGETTING FACTOR

integrated with the solution of the open-loop differential equation to result in the actually retained information y:

$$y = x\, e^{-bt} \tag{3}$$

Another way of modelling the forgetting factor is to represent it in a similar way to an output leak in a tank through an output valve, as shown in Figure 1. Hence, the model of an open-loop lecture that includes the forgetting factor effect as an output leak can be written as follows:

$$\frac{dx}{dt} = a(u - f), f = k\sqrt{x} \tag{4}$$

where u is the control input (a teacher variable related to the information delivery speed) and the forgetting factor is represented by f, which is a function of the retained information. The function f is modelled in a similar way as the outflow rate (leak) of a tank which is dependent on the liquid level. Simulations of models in Equation (3) and Equation (4) of an open-loop lecture are shown in Figure 3.

The simulations show the decay in retained information over a period of seven days after one hour of teaching. The curves represent different values of the parameters k and b accordingly. The values are arbitrarily chosen for the sole purpose of simulation; hence, quantitative conclusions cannot be obtained. However, qualitative and conceptual evaluations can be made. The simulation of the engineering model of the forgetting phenomenon as described in Equation (4) shows similar behaviour to the exponential decay of Equation (3). Hence, viewing the forgetting phenomenon as a leaking process can be as equally logical as viewing it as a decaying process.

The simulations in Figure 3 show the significant negative impact of the forgetting factor on retaining information in an open-loop lecture. Without rehearsal, most information will be lost over time.

Modelling a Closed-Loop Lecture

A closed-loop lecture here is considered to be implemented pedagogically in a constructivist student-centred approach which involves learners actively in the learning process and is distinguished with effective feedback and reflection practices. Mathematically speaking, the integrator (or the knowledge constructor) in this case will be the student. Once the student is given specific and clear learning objectives by the instructor, he/she will work on constructing mental models that build up the required learning objectives of the lecture.

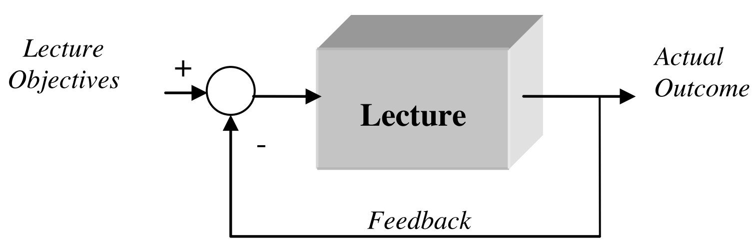

FIGURE 4
A MODEL OF CLOSED LOOP LECTURE FROM CONTROL ENGINEERING PERSPECTIVE

The student will be fed back with necessary information about the constructed mental models (internal or external feedback) upon assessment. Hence, the student will have an estimation of the gap between what has been actually learnt and what should have been learnt from the lecture. This information about the gap constitutes the control input to the student from a control systems perspective. The student continues the

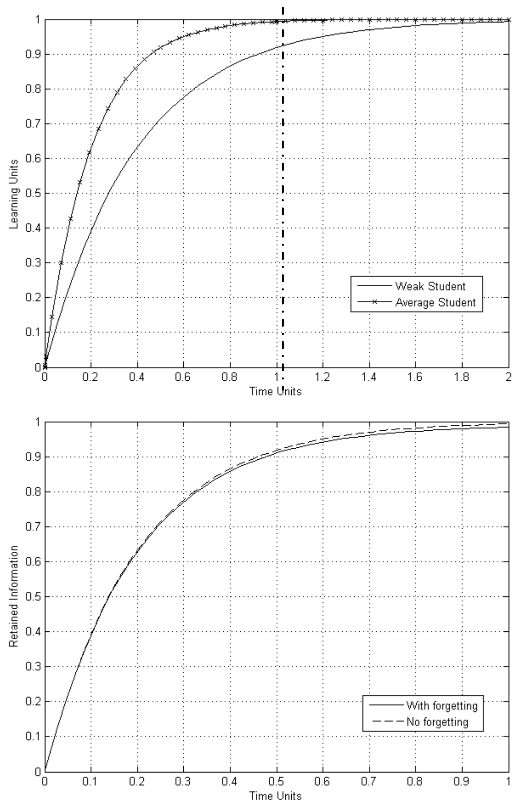

FIGURE 5

Top figure: Simulation of a Low-Capability Student's Achievement vs. an Average Student's Achievement in a Closed-loop Learning Mode. Bottom Figure: Closed-loop Learning with the Forgetting Factor and without the Forgetting Factor. The Forgetting Factor Value b = 0.03 was used for an Exponential Decaying Forgetting Model, as Given by Equation (5)

construction process until the actual learning outcome is identical to the set of learning objectives. Figure 4 shows a conceptual model of a closed-loop lecture from a systems perspective. The process can be mathematically modelled as follows:

$$\frac{dx}{dt} = -a'x + r \tag{5}$$

where x is an internal state representing the actual learning level (already constructed knowledge), r is the learning objective (goal) and a' is the learning constant that may differ from one student to another.

If considering the impact factor, the model would be rewritten as follows with regard to Ebbinghaus' exponential function:

$$\frac{dx}{dt} = -a'x\, e^{-bt} + r \tag{6}$$

If considering forgetting as a leaking phenomenon, the model can be rewritten as follows:

$$\frac{dx}{dt} = -a'\left(x - k\sqrt{x}\,\right) + r \tag{7}$$

In the analogy of a filling tank system, the pump in this case is mainly the student. The teacher, however, plays a coordinating role by setting the learning objectives, the learning resources (e.g. the source from which the pump will transfer the liquid) and assists in assessing the learner and giving feedback about the gap between what has been learnt and the learning objectives. In this case, the student plays a greater role in controlling the learning process.

The closed-loop model of lecturing holds two main advantages compared to the open-loop model from a control systems perspective: The closed-loop learning model of an accumulating process is an asymptotically stable system [34]. This means that the student will reach the defined set of learning objectives when constructing knowledge. This also implies that if the system deviates from its target, it will correct itself to get back to the desired objectives due to the feedback loop.

The closed-loop model is robust, which means that the model's uncertainty can be overcome by the feedback loop [35]. The robustness implication is that the gap between low-achieving and average students can be reduced by fostering feedback. In other words, closed-loop learning is convergent compared to open-loop learning.
Furthermore, the effect of the forgetting factor can be limited or ignored in the case of closed-loop learning compared to open-loop learning; this will be demonstrated through simulations.

Let's assume that the actual learning ability (ability of accumulating knowledge or achieving progress) for one student is about 50% weaker than the presumed average of the class, e.g. the constant a' in Equation (6) is 50% less. The simulations in Figure 5 (top) show that the 50% weaker student will lag less than 10% behind the average students by the end of the assigned learning time (e.g. one week for a lecture). If more time is allowed, the weaker student will finally reach the asymptotic stable point similar to the average students. This is different to the open-loop learning model, where the weaker student will lag significantly behind the average class, as discussed in the previous section.

The simulation in Figure 5 (bottom) shows the negligible effect of the forgetting factor in the case of feedback compared with feedback with no forgetting. The forgetting factor value used in this simulation is the same for the curve in the bottom graph in Figure 5, i.e. b = 0.03. Basically, feedback works here on detecting any gap in information between the actual learning outcome and the learning objectives due to forgetting, and the construction process would work on remedying this gap. The next section builds upon the developed open- and closed-loop models of a lecture and provides a collective model of a lecturing module assumed to be composed of 12 lectures.

THE PROCESS OF A SERIES LECTURES IN OPEN- AND CLOSED-LOOP MODES

Let us consider a module comprising 12 lectures spanned over one semester (e.g. one lecture per week for three months). Each lecture aims to accumulate a defined amount of information and depends upon the material learnt in the previous lecture as a prerequisite to reaching the new learning objectives. A conceptual model of such a series of lectures conducted in the open-loop mode is shown in Figure 6. The input of the model is a pulse of information flow (e.g. lasting one hour for a pulse of information) during the lecture. This pulse is repeated every week (if the course comprises one lecture per week), as shown in Figure 7. The accumulated information delivered by the lecturer is shown as stair's steps. The graph also represents the accumulated information in the student's mind under the influence of the forgetting phenomenon. The simulations show low information retention, i.e. 10% to 20% of the total delivered information.

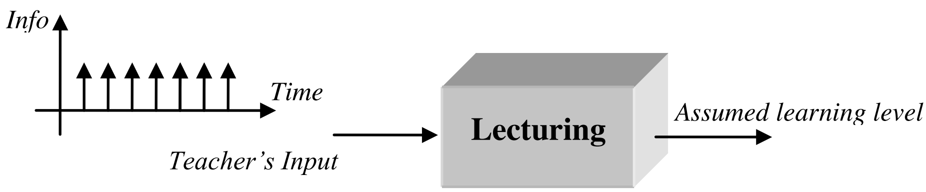

FIGURE 6
OPEN-LOOP LECTURING IS MODELLED AS A PROCESS WITH TEACHER INPUT AND AN OUTPUT REPRESENTING THE STUDENT'S LEARNING LEVEL

Let's assume that the module is designed in a way that develops effective student feedback and reflection on the taught lectures during the teaching period. Let's also assume that the students put effort during the course period into learning, immersing themselves in active experiential learning and continuously practising feedback and reflection. Thus, such a lecturing process is of a closed-loop nature and can be viewed as shown in Figure 8.The state space model of the 12-lecture module in the closed-loop form can be written as follows:

$$\begin{bmatrix} \dot{x_1} \\ \dot{x_2} \\ \dots \\ \dot{x_{12}} \end{bmatrix} = \begin{bmatrix} -a'_1 & 0 & \dots & 0 \\ 1 & -a'_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & -a'_{12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_{12} \end{bmatrix} e^{-bt} + \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} r_1 \\ r_2 \\ \dots \\ r_{12} \end{bmatrix} \qquad (8)$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_{12} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_{12} \end{bmatrix} \quad (9)$$

where $x_i, i = 1,2,..,12$, are the dynamical internal states representing the constructed knowledge for each lecture, Y represents the measurements of the students' actual learning level taken lecture-by-lecture and $r_i, i = 1,2,..,12$ are the learning objectives of the lectures. Notice that the system matrix in (8) is a lower triangular; its eigen-values

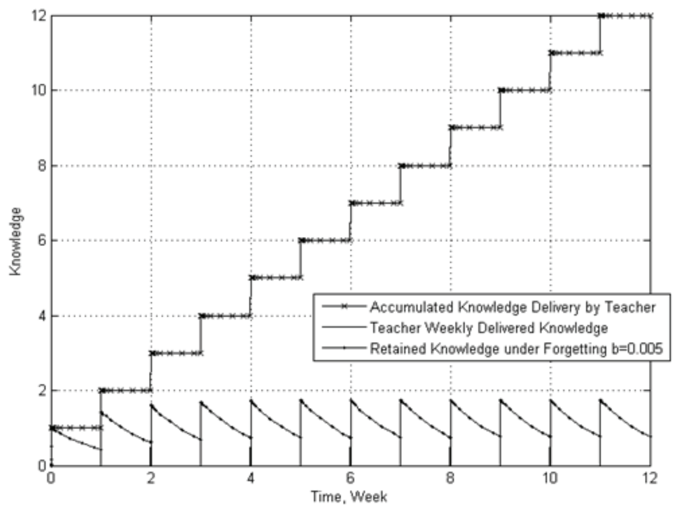

FIGURE 7
OPEN-LOOP LECTURING. THE FIGURE SHOWS THE DELIVERED ACCUMULATED INFORMATION, TEACHER INPUT, AND THE ACTUALLY RETAINED INFORMATION WITH THE PRESENCE OF THE FORGETTING FACTOR

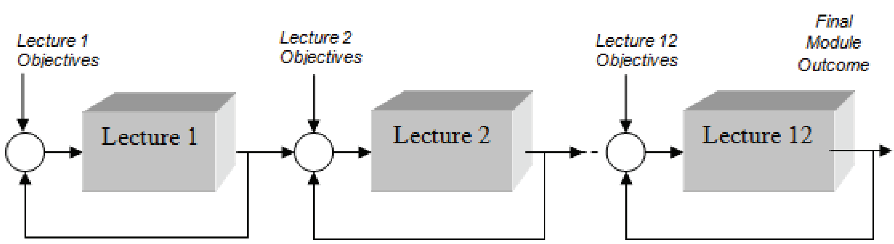

FIGURE 8
CLOSED-LOOP LECTURING OF A COURSE WHICH IS MODELLED AS A CASCADED PROCESS COMPOSED OF MANY STAGES WITH NEGATIVE FEEDBACK LOOP FOR EACH SUB STAGE

are represented by the main diameter: $\lambda_i = -a_i$ where $i = 1,2,..,12$. All eigen-values are strictly negative; hence the system is asymptotically stable [31], which means that in such a model of lecturing, students are more likely to achieve the set learning objectives. To show the robustness characteristic of a closed-loop series of lectures, a simulation of average vs. a 50% weaker student is shown in Figure 9. In both simulations, the value of the forgetting factor b was set to 0.005, which is equal to the simulation of the open-loop lecturing model shown in Figure 7. Despite the lower capability the weaker students, they could achieve a performance close to the average students due to the loop closure. By the end of the module, both average and weak students are able to meet the total learning objectives despite the presence of the forgetting factor.

The simulations of the open- and closed-loop lecturing models clearly show the advantages of adapting modern teaching and learning practices that close the loop. However, this task is not trivial. Closing the loop requires comprehensive assessment and evaluation practices and applying novel constructivist teaching and learning methods.

This requires a greater demand on the teacher as well as elaborated effort. The use of learning technologies and the philosophy of distributed control (e.g. peer assessment and service learning etc.) may assist significantly to overcome these obstacles.

Some Practical Ways for Closing the Loop

Many methods can be used to close the loop in the learning during the lecturing process along the semester progress, i.e. for establishing feedback and enhancing self-construction of knowledge. Enhanced loop closure can be achieved by pedagogical modifications of the learning or educational process (e.g. moving from the lecturing from a teacher-centered as in the open-loop model towards a student-centered approach as in the closed loop model), the use of learning technologies for facilitating assessment and cyclic learning, and the implementation of relevant pedagogical models. Pedagogical modifications may include the utilizatation of experiential and constructivist models, e.g. similar to those explained in [19, 21], using more frequent formative assessment [22], training students on self-regulated learning skills and self-construction of knowledge [36], establishment of effective feedback [37], and systematically designing the instruction or curricula [38]. Learning technologies can play an essential role in closing the loop and facilitating cyclical closed-loop learning. Simple technologies such as recorded audio lectures played on an mp3 player can be significantly effective in facilitating cyclic student-oriented learning experience [39]. Learning technologies can help to implement automatic feedback schemes, e.g. e-assessment and feedback such as explained in [40]. In our opinion, the blend of technology with proper pedagogical models is one of the best ways for maximizing the loop closure, one emergent area that is particularly focusing on this issue is Orchestrated Learning [41]. The following section summarizes the implication of the closed-loop model, and provides empirical findings of pedagogical research studies that been investigating the impact of some the ways for closing the loop that were stated earlier in this section.

Empirical Findings from Relevant Pedagogical Research

The main conclusions of the previous mathematical analysis of two extreme models of conducting lectures are: 1- The better the loop is closed, the more learning is attained; and 2- the closed-loop model can bridge the gap between higher and lower achievers. In this section, we bring some of the empirical findings from pedagogical research on relevant topics to the proposed thesis in this study, such as: assessment and educational feedback, constructivist learning, cyclic learning, educational technologies, and self-regulated learning (SRL).

Stoeger and Ziegler [42] investigated the impact of using the cyclic SRL model of Zimmerman et al. [43] on mathematics teaching and learning of fourth grade school pupils in Germany. The model emphasizes self-regulatory practices such as monitoring and self-evaluation, goal-setting and strategic planning, strategy implementation and monitoring and outcome monitoring. The study involved a control group and an experimental group formed from pupils of schools in Germany. The experimental group was trained for five weeks to use SRL techniques during a mathematics course, while the control group received no training. Both groups had to solve similar weekly assignments and quizzes. Two tests were conducted for the students of both groups, the first prior to the training and the second after the five-week period. In the German grading system, the highest grade is 1 and the lowest is 6, where 5 is the failure threshold. The control group students' test results average dropped from 2.37 for test 1 to 3.11 for test 2 (p-value < 0.001) while the experimental group students' test average was stable and showed a small enhancement, 2.68 for test 1 to 2.63 for test 2 (p-value > 0.10). These results show how enhanced closure of the feedback loop leads to a stable performance and eliminates the forgetting factor represented by reduced achievement of the control group in test 2; similarly to what has been analyzed in the open-loop model discussed earlier. The study reports that the weak students of the self-regulation training group who had to take an entrance exam to gain entry to a higher school (as they were unable to attain the needed composite score) ALL passed. Normally, 50% score below the pass rate of the entrance exam every year; this was the first time that ALL students passed the entrance exam. This indicates that enhanced closure of the loop reduced the gap between the weak and average students, similarly to the analyzed outcomes of the closed-loop model. The analysis of the weekly assignments and quizzes of the students in the experimental group revealed a linear increase in the solution rate of the mathematical problems over the course of the five weeks; the linear growth slowed down towards the end of the training. These findings are compatible with the growth of the closed-loop learning curve, as shown in Figure 5.

McKinney et al. [39] investigated the learning outcomes of listening to psychology lectures via podcasts without lecture attendance (experimental group) vs. attending the lecture but no podcasts (control group). The results were reported through the average means and standard deviation (SD) of the groups. About two thirds of the experimental group students listened to the recording of the lecture twice or more (more cycles), while the control group students had only one access to the lecture via attendance (they were not provided with audio records). Both groups were tested; the experimental group average was 71.24% (SD = 16.50%) while the control group average was 62.47% (SD = 17.03%), with p-value < 0.05, indicating a statistically significant difference. Within the experimental group there were students who took notes alongside the lecture and students who took no notes. The comparison of the test results between the two groups (notes, no notes) revealed an average 76.23% (SD = 13.61%) for the note-taking group and 62.08% (SD = 17.93%) for the no notes group. Listening to a lecture more than once and/or taking notes are practices of cyclic learning and involve more reflection and feedback than listening to a lecture once or taking no notes (open-loop learning). McKinney et al.'s

[39] findings support the hypothesis of the closed-loop model of enhanced learning vs. the open-loop model. Furthermore, the standard deviation (SD) in that study shows that the more feedback and reflection is practiced by learners, the lower the dispersion or gap in achievement is among the group members (i.e. more convergent learning outcomes).

Krause et al. [44] conducted a controlled experiment on the effect of feedback intervention on e-learning in a statistics course. The control group students worked on six problem-solving tasks on correlation analysis. Once a task was completed, students had access to a worked example of the same nature so they could evaluate their solutions, thus the control group students had some feedback available. The experimental group students were exposed to the same procedure plus an additional feedback treatment composed of six multiple-choice tests with adaptive and elaborated feedback. On a scale of 20, the pre-test of the control and experimental group showed equivalence, 4.28 (SD = 2.13) for the control group, 4.24 (SD = 2.33) for the experimental group with p-value > 0.05. The post-test, however, revealed a significant impact of feedback intervention on students' learning. The control group students averaged 10.25 (SD = 3.41) while the experimental group students averaged 14.51 (SD= 2.15) with p-value < 0.05. Furthermore, analysis of the students results in terms of low- and high-level prior knowledge show that feedback benefited low-level students significantly in bridging the gap and reaching a level similar to the high-level students in the post-test. In the control group, the low-level students averaged 8.85 (SD = 3.63) in the post-test and the high level students averaged 12.25 (SD = 1.81) with p-value < 0.05, while in the experimental group, the low-level students averaged 14.25 (SD = 1.92) and the high-level students averaged 14.84 (SD = 2.5) with p-value > 0.05. Krause et al.'s (2009) findings support the hypothesis of the closed-loop model that better enhancement of loop closure leads to higher achievement and bridges the gap between students of different levels.

Abdulwahed and Nagy [19] proposed a constructivist laboratory education model based on Kolb's [18] experiential learning cycle. Kolb defines learning as "the process whereby knowledge is created through transformation of experience" and suggested that effective learning should pass a cycle of four phases: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC) and Active Experimentation (AE). Kolb derived his model based on Lewin's [45] social and pedagogical works. Lewin borrowed the control engineering concepts such as reference signals, measurements and feedback to develop a four-stage model of learning that later became the core basis of Kolb's experiential learning cycle [18]. The application of the model into teaching and learning of laboratory education included one cyclic opportunity by means of a virtual lab; however it has resulted in enhanced outcome of the laboratory report mark and the final exam mark of the module for the experimental group vs. the control group. For the laboratory report mark, the control group students' average was 63.03% (SD = 7.42, N = 65), while the experimental group students' average was 67.28% (SD = 5.19, N = 46, p-value = 0.002 < 0.05). For the mark of the final exam of the module, the control group students' average was 48.40% (SD = 21.27, N = 65), while the experimental group students' average was 58.47% (SD = 20.40, N = 46, p-value = 0.018 < 0.05). These data shows that enhanced closure of the loop by means of an additional cyclic learning opportunity, which was facilitated via computer assisted learning method (virtual lab in this case), has resulted enhanced learning outcome and smaller standard deviation (e.g. convergent learning).

DISCUSSION

The empirical studies from the pedagogical research outlined in the previous section provide an indicative quantitative evidence of the stated hypothesis of open- and closed-loop models developed earlier in this study. It is worth mentioning that the developed mathematical models of open- and closed-loop lecturing are rather a significant simplification of a human-centered complex process, which also involves high uncertainties.

However, even in technical systems, control engineering models are in many cases produced with significant simplification of the modeled complex system. Control engineering tools utilize specific regulatory algorithms to handle uncertainties of the process and its modeled parameters. One of the most used regulatory algorithms is to restructure the system via introducing a controller and implementing a negative feedback that compares its outcomes with its objectives.

In this study, we have shown that a control engineering approach could be also utilized for analyzing and designing an enhanced learning system (lecturing process in this case) similarly to technical systems via: 1- restarting the system through providing students with more control of their learning (constructivist student-centred approach); and 2- implementing effective assessment and feedback. While the positive impact of constructivist student-centered methods, and assessment and feedback have been frequently reported in the pedagogical literature, approaching these issues from control engineering perspectives provide a new aspects in which systems theory tools are utilized.

Researchers could use the proposed models in this study as a starting point where more complex regulatory algorithms from control engineering could be developed and applied to learning systems. Some potential areas of relevance from systems and control theory could be “Systems Identification”, “Adaptive Control”, “Robust Control”, “Fuzzy Control”, just to name few. System identification methods [46] are normally utilized for obtaining the values of the system parameters. Adaptive control methods [47] are used to design and deploy adaptive regulatory algorithms that change dynamically when the system’s parameters change over time. Robust control methods [48] are used to design and deploy regulatory algorithm that guarantee the achievement of the system’s objectives despite high uncertainties in the modeled process. Fuzzy control [49] methods similarly aims to enforce the system to meet its objective, they are more utilized with systems that are difficult to model mathematically. The mathematical models developed in this study could contribute to the emergent field of Learning Analytics [50]. In learning analytics, new quantitative methods are utilized to model, analyze, and design learning systems.

It is also hoped that the control systems–to–learning systems approach illustrated here could stimulate engineering academics and educators from other engineering domains to consider the utilization of their disciplinary engineering tools and methods in learning systems. It is expected that such kind of transformative research could have a significant contribution to the learning sciences [51].

SUMMARY

We have introduced a new approach of using control systems methods for modelling in pedagogy, with a case applied to the lecturing process. The case for modelling lecturing is developed with the focus on two extremes: so-called open- and closed-loop lecturing. The modelling process of lecturing was conducted in a similar way to engineering modelling; the tank example was selected for illustration. The analysis of the models showed the advantages of the closed-loop lecturing model vs. the open-loop learning model in conjunction with three main issues. The closed-loop lecturing process is stable, holds an inherent disturbance rejection mechanism (e.g. against forgetting) and is robust. A new model of forgetting, based on an engineering concept, is introduced. Empirical findings from relevant pedagogical literature provide an indicative support of the developed hypotheses of open- and closed-loop models. Future work is planned to develop the proposed models further and investigate their implications in real-life settings.

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